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(54) **SYSTEM AND METHOD FOR MULTIMEDIA RANKING AND MULTI-MODAL IMAGE RETRIEVAL USING PROBABILISTIC SEMANTIC MODELS AND EXPECTATION-MAXIMIZATION (EM) LEARNING**

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(60) Provisional application No. 60/763,848, filed on Jan. 31, 2006.

(51) **Int. Cl.**

G06F 15/18	(2006.01)
G06F 17/30	(2006.01)
G06K 9/62	(2006.01)

(52) **U.S. Cl.**
CPC ***G06F 17/30256*** (2013.01); ***G06K 9/6278*** (2013.01)

(58) **Field of Classification Search**
CPC G06F 17/30256; G06F 17/30017; G06F 17/30253; G06K 9/6278
USPC 706/12, 45
See application file for complete search history.

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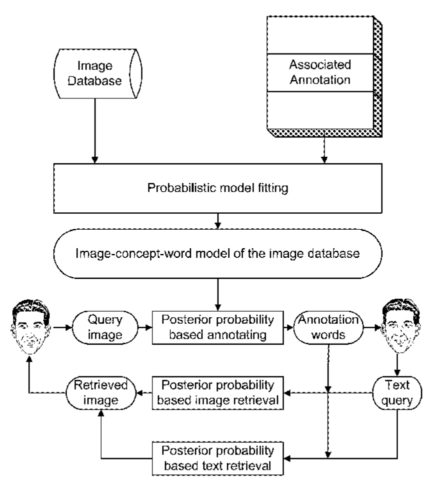
(57) **ABSTRACT**

Systems and Methods for multi-modal or multimedia image retrieval are provided. Automatic image annotation is achieved based on a probabilistic semantic model in which visual features and textual words are connected via a hidden layer comprising the semantic concepts to be discovered, to explicitly exploit the synergy between the two modalities. The association of visual features and textual words is determined in a Bayesian framework to provide confidence of the association. A hidden concept layer which connects the visual feature(s) and the words is discovered by fitting a generative model to the training image and annotation words. An Expectation-Maximization (EM) based iterative learning procedure determines the conditional probabilities of the visual features and the textual words given a hidden concept class. Based on the discovered hidden concept layer and the corresponding conditional probabilities, the image annotation and the text-to-image retrieval are performed using the Bayesian framework.

22 Claims, 4 Drawing Sheets



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Srihari, Use of Multimedia Input in Automated Image Annotation and Content-Based Retrieval, 1995, IS&T/SPIE's Symposium on Electronic Imaging: Science & Technology, International Society for Optics and Photonics, pp. 249-260.*

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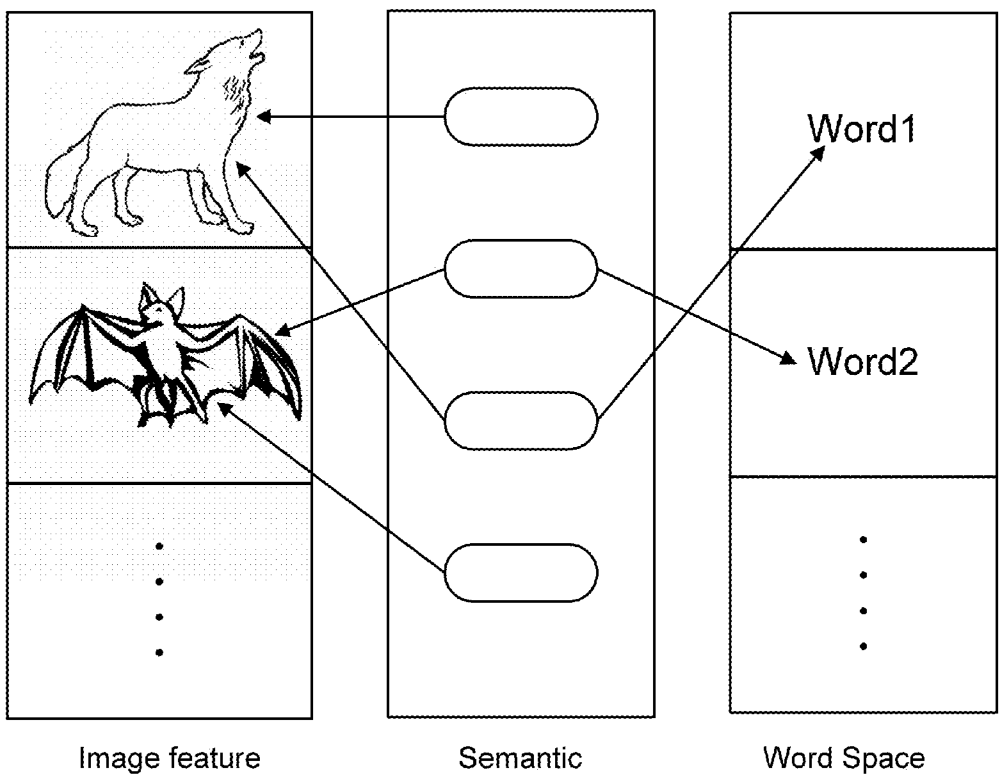

Fig. 1

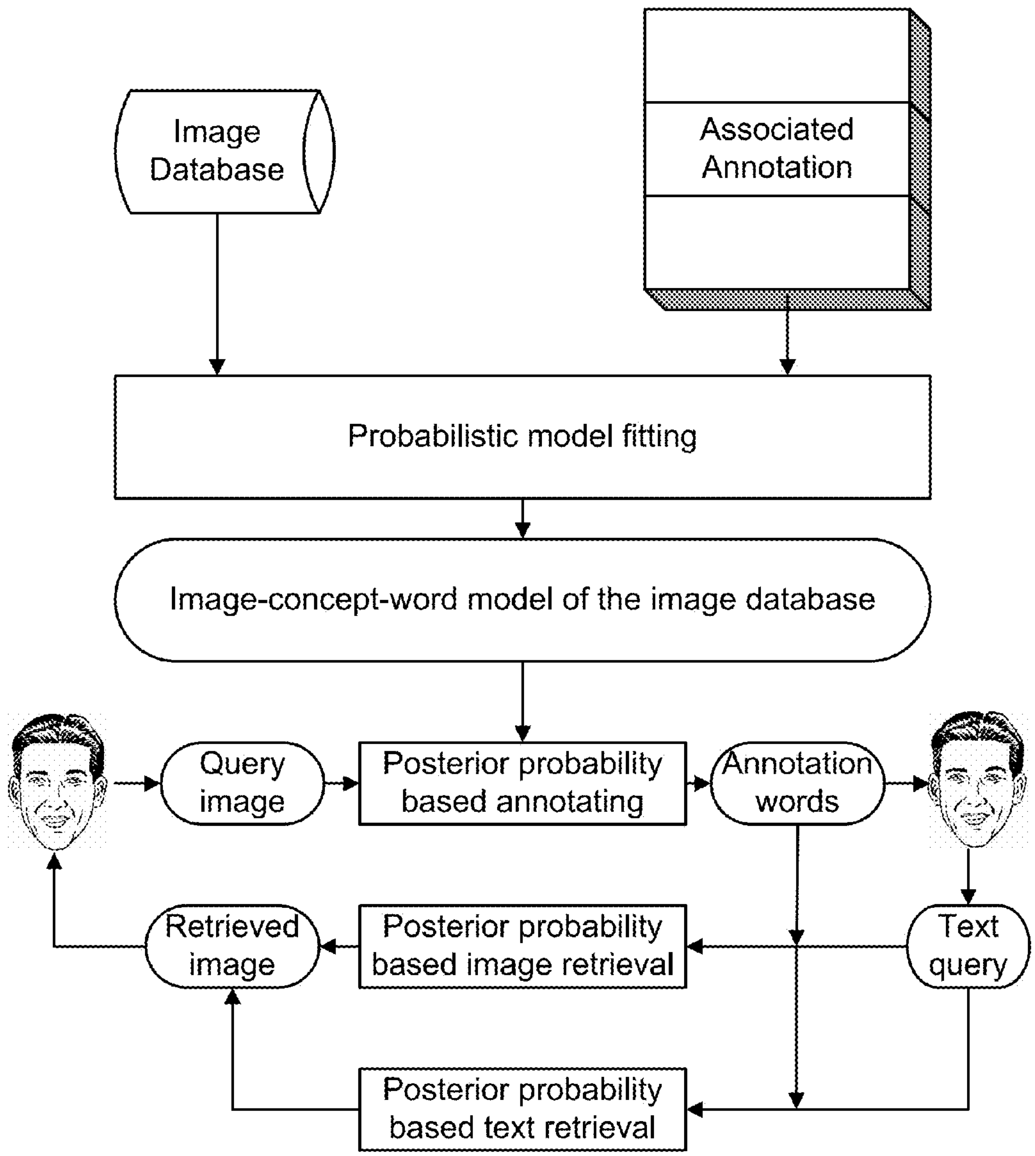
Image Database
Associated Annotation
Probabilistic model fitting
Image-concept-word model of the image database
Query image
Posterior probability based annotating
Annotation words
Retrieved image
Posterior probability based image retrieval
Text query
Posterior probability based text retrieval

Fig. 2

{people(6), mountain(6), sky(5), outdoor(7), rocky(4), snow-capped(2)}

Fig. 3

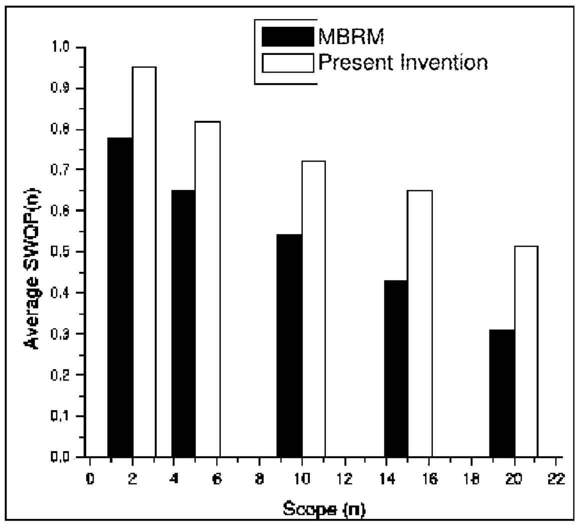

Fig. 4

System					
MBRM	animal water wolf house tiger	male-face hair people bear sky	bird grass leopard sail cuckoo	flower red tree meadow outdoor	desert beach mummy building church
Present Invention	wolf winter wild animal stone	male-face people hair man mono-logue	bird cuckoo yel-low sand sky	flower red azalea leaf landscape	pyramid Egypt desert mummy beach

Fig. 5

SYSTEM AND METHOD FOR MULTIMEDIA RANKING AND MULTI-MODAL IMAGE RETRIEVAL USING PROBABILISTIC SEMANTIC MODELS AND EXPECTATION-MAXIMIZATION (EM) LEARNING

CROSS REFERENCE TO RELATED APPLICATIONS

The present application is a Continuation of U.S. patent application Ser. No. 12/903,099, filed Oct. 12, 2010, now U.S. Pat. No. 8,204,842, issued Jun. 19, 2012, which is a Continuation of U.S. patent application Ser. No. 11/626,835, filed Jan. 24, 2007, issued Oct. 12, 2010 as U.S. Pat. No. 7,814,040, which is a non-provisional application claiming benefit of priority from U.S. Provisional Patent Application Ser. No. 60/763,848, filed Jan. 31, 2006, each of which is expressly incorporated herein in their entirety.

BACKGROUND OF THE INVENTION

Efficient access to multimedia database content requires the ability to search and organize multimedia information. In one form of traditional image retrieval, users have to provide examples of images that they are looking for. Similar images are found based on the match of image features. This retrieval paradigm is called Content-Based Image Retrieval (CBIR). In another type of retrieval system, images are associated with a description or metadata which is used as a surrogate for the image content.

It is noted that audio retrieval systems may also employ pattern recognition and content extraction. Typically, the content extraction operates on a direct semantic level, e.g., speech recognition, while source modeling and musical structure extraction may also be employed. Rarely, however, are implicit semantic concepts derived independently of the express semantic structures expressly presented in the audio sample.

Even though there have been many studies on CBIR, empirical studies have shown that using image features solely to find similar images is usually insufficient due to the notorious gap between low-level features and high-level semantic concepts (called semantic gap) [21]. In order to reduce this gap, region based features (describing object level features), instead of raw features of whole image, to represent the visual content of an image is proposed [5, 22, 7].

On the other hand, it is well-observed that often imagery does not exist in isolation; instead, typically there is rich collateral information co-existing with image data in many applications. Examples include the Web, many domain archived image databases (in which there are annotations to images), and even consumer photo collections. In order to further reduce the semantic gap, recently multi-modal approaches to image retrieval are proposed in the literature [25] to explicitly exploit the redundancy co-existing in the collateral information to the images. In addition to the improved retrieval accuracy, another benefit for the multimodal approaches is the added querying modalities. Users can query an image database either by image, or by a collateral information modality (e.g., text), or by any combination.

In addition to static image retrieval, proposals and systems have been developed to handle object identification, extraction, characterization, and segment retrieval in video programs and samples. In general, these systems directly extend the static image and audio techniques, although they may gain benefit of synchronization and association of audio and video

data (and possibly closed caption text, if available) Likewise, analysis of temporal changes allows extraction of objects, analysis of object degrees of freedom, and motion planes within the signal. See, U.S. Pat. Nos. 6,850,252; 6,640,145; 6,418,424; 6,400,996; 6,081,750; 5,920,477; 5,903,454; 5,901,246; 5,875,108; 5,867,386; and 5,774,357, expressly incorporated herein by reference. Automated annotation of images and video content may be used in conjunction with MPEG-7 technologies.

Another use of object identification techniques is to permit efficient compression and/or model-based representation of objects within an image or video stream. Thus, especially in information loss-tolerant compression schemes, an image may be compressed in a vector quantized scheme by representing an object with a symbol (e.g., a word). The symbol, of course, may include a variety of parameters, for example describing scaling, translation, distortion, orientation, conformation, etc, as well as providing an error vector to establish deviance of the original image from the symbol (or model) representation.

A number of approaches have been proposed in the literature on automatic image annotation[1, 10, 11, 17]. Different models and machine learning techniques are developed to learn the correlation between image features and textual words from the examples of annotated images and then apply the learned correlation to predict words for unseen images. The co-occurrence model [19] collects the co-occurrence counts between words and image features and uses them to predict annotated words for images. Barnard and Duygulu et al[1, 10] improved the co-occurrence model by utilizing machine translation models. The models are correspondence extensions to Hofmann's hierarchical clustering aspect model [14, 15, 13], which incorporate multimodality information. The models consider image annotation as a process of translation from "visual language" to text and collect the co-occurrence information by the estimation of the translation probabilities. The correspondence between blobs and words are learned by using statistical translation models. As noted by the authors [1], the performance of the models is strongly affected by the quality of image segmentation. More sophisticated graphical models, such as Latent Dirichlet Allocator (LDA) [3] and correspondence LDA, have also been applied to the image annotation problem recently [2]. Another way to address automatic image annotation is to apply classification approaches. The classification approaches treat each annotated word (or each semantic category) as an independent class and create a different image classification model for every word (or category).

One representative work of these approaches is automatic linguistic indexing of pictures (ALIPS) [17]. In ALIPS, the training image set is assumed well classified and each category is modeled by using 2D multi-resolution hidden Markov models. The image annotation is based on nearest-neighbor classification and word occurrence counting, while the correspondence between the visual content and the annotation words is not exploited. In addition, the assumption made in ALIPS that the annotation words are semantically exclusive may not be necessarily valid in nature.

Recently, relevance language models [11] have been successfully applied to automatic image annotation. The essential idea is to first find annotated images that are similar to a test image and then use the words shared by the annotations of the similar images to annotate the test image.

One model in this category is Multiple-Bernoulli Relevance Model (MBRM) [11], which is based on the Continuous space Relevance Model (CRM) [16]. In MBRM, the word probabilities are estimated using a multiple Bernoulli model and the image block feature probabilities using a nonparametric kernel density estimate. The reported experiment shows that MBRM model outperforms the previous CRM model, which assumes that annotation words for any given image follow a multinomial distribution and applies image segmentation to obtain blobs for annotation.

It has been noted that in many cases both images and word-based documents are interesting to users' querying needs, such as in the Web search environment. In these scenarios, multi-modal image retrieval, i.e., leveraging the collected textual information to improve image retrieval and to enhance users' querying modalities, is proven to be very promising. Some studies have been reported on this problem.

Chang et al[6] applied a Bayes point machine to associate words and images to support multi-modal image retrieval. In [26], latent semantic indexing is used together with both textual and visual features to extract the underlying semantic structure of Web documents. Improvement of the retrieval performance is reported attributed to the synergy of both modalities. Recently, approaches using multi-modal information for Web image retrieval are emerging. In [23], an iterative similarity propagation approach is proposed to explore the inter-relationships between Web images and their textual annotations for image retrieval. The mutual reinforcement of similarities between different modalities is exploited, which boosts the Web image retrieval performance.

Appendix A provides a list of references relating to content-based image retrieval [CBIR], and latent semantic indexing, each of which is expressly incorporated herein by reference.

SUMMARY OF THE INVENTION

The present invention provides systems and methods for probabilistic semantic modeling of image information and the corresponding learning procedure to address the problem of automatic image annotation and its application to multimodal image retrieval.

The probabilistic semantic model preferably exploits the synergy between the different modalities of the imagery and the collateral information.

While the preferred embodiment focuses on a specific collateral modality—text, it should be apparent that any other collateral modalities, such as audio, time-sequences, hyperlink and reverse-hyperlink analysis, etc. The model may thus be generalized to incorporating other collateral modalities.

Consequently, the synergy here is explicitly represented as a hidden layer between the image and the text modalities. This hidden layer constitutes the concepts to be discovered through a probabilistic framework such that the confidence of the association can be provided. While a preferred embodiment employs unconstrained concepts, it should be apparent that taxonomies, hierarchies, vocabularies, and other intrinsic or extrinsic conceptual frameworks may be provided, either to expressly limit the concepts within the hidden layer, or as an adjunct to the unconstrained concepts. It should also be apparent that, while a single hidden layer is sufficient for the preferred embodiment, multiple hidden layers and/or partial additional layers may be implemented in known manner.

An Expectation-Maximization (EM) based iterative learning procedure is preferably employed to determine the conditional probabilities of the visual features and the words given a hidden concept class. Based on the discovered hidden concept layer and the corresponding conditional probabilities, the image-to-text retrieval and text-to-image retrieval are performed in a Bayesian framework.

While the preferred embodiment relates images to words, it is understood that the input and output of the system are not limited thereby, and the methods and systems described herein may be used to relate any two modalities linked through a hidden concept layer. Likewise, the system is not limited to simply outputting a word set associated with an image, or an image set associated with a word, but rather may be employed within a larger and more complex system to provide automated data processing and/or to implement a control system.

In recent CBIR literature, Corel data have been extensively used to evaluate the retrieval performance [1, 10, 11, 17]. It has been argued [24] that the Corel data are much easier to annotate and retrieve due to its relatively small number of concepts and relatively small variations of visual contents. In addition, the relatively small number (1000 to 5000) of training images and test images typically used in the literature further makes the problem easier and the evaluation less convictive.

In order to truly capture the difficulties in real scenarios such as Web image retrieval and to demonstrate the robustness and promise of the inventive model and framework in these challenging applications, a prototype system is evaluated on a collection of 17,000 images with the automatically extracted textual annotation from various crawled Web pages. The model and framework according to the present invention work well in this scale, even considering the very noisy image data set, and substantially outperforms the state-of-the-art peer system MBRM [11].

To achieve the automatic image annotation as well as multimodal image retrieval, a probabilistic semantic model is provided for the training image and the associated textual word annotation dataset. The preferred probabilistic semantic model is developed by the EM technique to determine the hidden layer connecting image features and textual words, which constitutes the semantic concepts to be discovered to explicitly exploit the synergy between imagery and text.

It is therefore an object of the present invention to provide a probabilistic semantic model in which the visual features and textual words are connected via a hidden layer to constitute the concepts to be discovered to explicitly exploit the synergy between the two modalities. An EM based learning procedure is developed to fit the model to the two modalities.

It is a further object of the invention to provide a system and method in which the association of visual features and textual words is determined in a Bayesian framework such that the confidence of the association can be provided.

BRIEF DESCRIPTION OF THE FIGURES

The invention will now be explained with reference to the figures, in which:

FIG. **1** shows a graphic representation of the model for the randomized data generation for exploiting the synergy between imagery and text;

FIG. **2** shows a block diagram of the architecture of the system;

FIG. **3** shows an example of image-annotation-word pairs in the generated database, in which the number following each word is the corresponding weight of the word;

FIG. **4** shows a graph of the average SWQP(n) comparisons between the prior art MBRM technique and the technique according to a preferred embodiment of the invention; and

FIG. **5** shows a table of examples of automatic annotations produced by the prior art MBRM technique and the technique according to a preferred embodiment of the invention.

DETAILED DESCRIPTION OF THE INVENTION

Probabilistic Annotated Image Model

As employed herein, f_i, $i\epsilon[1, N]$ denotes the visual feature vector of images in the training database, where N is the size of the database. w^j, $j\epsilon[1,M]$ denotes the distinct textual words in the training annotation word set, where M is the size of annotation vocabulary in the training database.

In the probabilistic model, we assume the visual features of images in the database, $f_i=[f_i^1, f_i^2, \ldots, f_i^L]$, $i\epsilon[1,N]$ are known i.i.d. samples from an unknown distribution.

The dimension of the visual feature is L. We also assume that the specific visual feature annotation word pairs (f_i, w^j), $i\epsilon[1,N]$, $j\epsilon[1,M]$ are known i.i.d. samples from an unknown distribution. Furthermore we assume that these samples are associated with an unobserved semantic concept variable $z\epsilon Z=\{z_1, \ldots z_k\}$. Each observation of one visual feature $f\epsilon F=\{f_1, f_2, \ldots, f_N\}$ belongs to one or more concept classes z_k and each observation of one word $w\epsilon V=\{w^1, w^2, \ldots, w^M\}$ in one image f_i belongs to one concept class. To simplify the model, we have two more assumptions. First, the observation pairs (f_i,w^j) are generated independently. Second, the pairs of random variables (f_i,w^j) are conditionally independent given the respective hidden concept z_k,

$$P(f_i,w^j|z_k)=P_{\mathfrak{F}}(f_i|z_k)P_V(w^j|z_k) \tag{1}$$

The visual feature and word distribution is treated as a randomized data generation process described as follows:

choose a concept with probability $P_z(z_k)$;

select a visual feature $f_i\,\epsilon F$ with probability $P_{\mathfrak{F}}(f_i|z_k)$; and

select a textual word $w^j\,\epsilon V$ with probability $P_V(w^j|z_k)$.

As a result one obtains an observed pair (f_i,w^j), while the concept variable z_k is discarded. The graphic representation of this model is depicted in FIG. **1**.

Translating this process into a joint probability model results in the expression

$$\begin{aligned} P(f_i, w^j) &= P(w^j)P(f_i \mid w^j) \\ &= P(w^j)\sum_{k=1}^{K} P_{\mathfrak{F}}(f_i \mid z_k)P(z_k \mid w^j) \end{aligned} \tag{2}$$

Inverting the conditional probability $P(z_k|w^j)$ in (2) with the application of the Bayes' rule results in

$$P(f_i, w^j) = \sum_{k=1}^{K} P_z(z_k)P_{\mathfrak{F}}(f_i \mid z_k)P_V(w^j \mid z_k) \tag{3}$$

The mixture of Gaussian[9] is assumed for the feature concept conditional probability $P_{\mathfrak{F}}(\bullet|Z)$. In other words, the visual features are generated from K Gaussian distributions, each one corresponding a z_k. For a specific semantic concept variable z_k, the conditional probability density function (pdf) of visual feature f_i is

$$P_{\mathfrak{F}}(f_i \mid z_k) = \frac{1}{2\pi^{L/2}\left|\sum_k\right|^{1/2}} e^{-\frac{1}{2}(f_i-\mu_k)^T \Sigma_k^{-1}(f_i-\mu_k)} \tag{4}$$

where Σ_k and μ_k are the covariance matrix and mean of visual features belonging to z_k, respectively. The word concept conditional probabilities $P_V(\bullet|Z)$, i.e., $P_V(w^j|z_k)$ for $k\epsilon[1, K]$, are estimated through fitting the probabilistic model to the training set.

Following the maximum likelihood principle, one determines $P_{\mathfrak{F}}(f_i|z_k)$ by maximization of the log-likelihood function

$$\log\prod_{i=1}^{N} P_{\mathfrak{F}}(f_i \mid Z)^{u_i} = \sum_{i=1}^{N} u_i \log\left(\sum_{k=1}^{K} P_z(z_k)P_{\mathfrak{F}}(f_i \mid z_k)\right) \tag{5}$$

where μ_i is the number of annotation words for image f_i. Similarly, $P_z(z_k)$) and $P_V(w^j|z_k)$ can be determined by maximization of the log-likelihood function

$$\mathfrak{L} = \log P(F, V) = \sum_{i=1}^{N}\sum_{j=1}^{M} n(w_i^j)\log P(f_i, w^j) \tag{6}$$

where $n(w_i^j)$ denotes the weight of annotation word w^j, i.e., occurrence frequency, for image f_i.

EM-Based Procedure for Model Fitting

From (5), (6) and (2) we derive that the model is a statistical mixture model [18], which can be resolved by applying the EM technique [8]. The EM alternates in two steps: (i) an expectation (E) step where the posterior probabilities are computed for the hidden variable z_k based on the current estimates of the parameters; and (ii) an maximization (M) step, where parameters are updated to maximize the expectation of the complete-data likelihood log P(F,V,Z) given the posterior probabilities computed in the previous E-step.

Thus the probabilities can be iteratively determined by fitting the model to the training image database and the associated annotations.

Applying Bayes' rule to (3), we determine the posterior probability for z_k under f_i and (f_i,w^j):

$$p(z_k \mid f_i) = \frac{P_z(z_k)P_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{t=1}^{K} P_z(z_t)P_{\mathfrak{F}}(f_i \mid z_t)P_V(w^j \mid z_t)} \tag{7}$$

$$p(z_k \mid f_i, w^j) = \frac{P_z(z_k)P_z(f_i \mid z_k)P_V(w^j \mid z_k)}{\sum_{t=1}^{K} P_z(z_t)P_{\mathfrak{F}}(f_i \mid z_t)P_V(w^j \mid z_t)} \tag{8}$$

The expectation of the complete-data likelihood log P(F,V,Z) for the estimated log P(F|V,Z) derived from (8) is

$$\sum_{(i,j)=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M} n(w_i^j)\log[P_z(z_{i,j})P_{\mathfrak{F}}(f_i \mid z_{i,j})P_V(w^j \mid z_{i,j})]P(Z \mid F, V) \tag{9}$$

where

$$P(Z\mid F,V)=\prod_{s=1}^{N}\prod_{t=1}^{M}P(z_{s,t}\mid f_s,w^t)$$

In (9) the notation $z_{i,j}$ is the concept variable that associates with the feature-word pair (f_i, w^j). In other words, (f_i,w^j) belongs to concept z_t where t=(i,j).

Similarly, the expectation of the likelihood log P(F,Z) for the estimated P(Z|F) derived from (7) is

$$\sum_{k=1}^{K}\sum_{i=1}^{N}\log(P_z(z_k)p_{\mathfrak{F}}(f_i\mid z_k))p(z_k\mid f_i) \tag{10}$$

Maximizing (9) and (10) with Lagrange multipliers to $P_z(z_l)$, $p_{\mathfrak{F}}(f_u|z_l)$ and $P_V(w^v|z_l)$ respectively, under the following normalization constraints

$$\sum_{k=1}^{K}P_z(z_k)=1,\ \sum_{k=1}^{K}P(z_k\mid f_i,w^j)=1 \tag{11}$$

for any f_i, w^j, and z_l, the parameters are determined as

$$\mu_k=\frac{\sum_{i=1}^{N}u_i f_i p(z_k\mid f_i)}{\sum_{s=1}^{N}u_s p(z_k\mid f_s)} \tag{12}$$

$$\sum_k=\frac{\sum_{i=1}^{N}u_i p(z_k\mid f_i)(f_i-\mu_k)(f_i-\mu_k)^T}{\sum_{s=1}^{N}u_s p(z_k\mid f_s)} \tag{13}$$

$$P_z(z_k)=\frac{\sum_{j=1}^{M}\sum_{i=1}^{N}u(w_i^j)P(z_k\mid f_i,w^j)}{\sum_{j=1}^{M}\sum_{i=1}^{N}n(w_i^j)} \tag{14}$$

$$P_V(w^j\mid z_k)=\frac{\sum_{N=i}^{N}n(w_i^j)P(z_k\mid f_i,w^j)}{\sum_{u=1}^{M}\sum_{V=1}^{N}n(w_V^u)P(z_k\mid f_V,w^u)} \tag{15}$$

Alternating (7) and (8) with (12)-(15) defines a convergent procedure to a local maximum of the expectation in (9) and (10).

Estimating the Number of Concepts

The number of concepts, K, must be determined in advance for the EM model fitting. Ideally, we intend to select the value of K that best agrees to the number of semantic classes in the training set. One readily available notion of the fitting goodness is the log-likelihood. Given this indicator, we can apply the Minimum Description Length (MDL) principle [20] to select among values of K. This can be done as follows [20]: choose K to maximize

$$\log(P(F,V))-\frac{m_K}{2}\log(MN) \tag{16}$$

where the first term is expressed in (6) and m_K is the number of free parameters needed for a model with K mixture components. In our probabilistic model, we have

$$m_K=(K-1)+K(M-1)+K(N-1)+L^2=K(M+N-1)+L^2-1$$

As a consequence of this principle, when models with different values of K fit the data equally well, the simpler model is selected. In our experimental database, K is determined through maximizing (16).

Model Based Image Annotation and Multi-Modal Image Retrieval

After the EM-based iterative procedure converges, the model fitted to the training set is obtained. The image annotation and multi-modal image retrieval are conducted in a Bayesian framework with the determined $P_z(z_k)$, $p_{\mathfrak{F}}(f_i|z_k)$, and $P_V(w^j|z_k)$.

Image Annotation and Image-to-Text Retrieval

The objective of image annotation is to return words which best reflect the semantics of the visual content of images.

According to one embodiment of the present invention, a joint distribution is used to model the probability of an event that a word w^j belonging to semantic concept z_k is an annotation word of image f_i. Observing (1), the joint probability is

$$P(w^j,z_k,f_i)=P_z(Z_k)p_{\mathfrak{F}}(f_i\mid z_k)P_V(w^j\mid z_k) \tag{17}$$

Through applying Bayes law and the integration over $P_z(z_k)$, we obtain the following expression:

$$\begin{aligned}P(w^j\mid f_i)&=\int P_V(w^j\mid z)p(z\mid f_i)dz \\ &=\int P_V(w^j\mid z)\frac{p_{\mathfrak{F}}(f_i\mid z)P(z)}{p(f_i)}dz \\ &=E_z\left\{\frac{P_V(w^j\mid z)p_{\mathfrak{F}}(f_i\mid z)}{p(f_i)}\right\}\end{aligned} \tag{18}$$

where

$$p(f_i)=\int p_{\mathfrak{F}}(f_i\mid z)P_z(z)dz=E_z\{p_{\mathfrak{F}}(f_i\mid z)\} \tag{19}$$

In above equations $E_z\{\bullet\}$ denotes the expectation over $P(z_k)$, the probability of semantic concept variables. (18) provides a principled way to determine the probability of word w^j for annotating image f_i. With the combination of (18) and (19), the automatic image annotation can be solved fully in the Bayesian framework.

In practice, an approximation of the expectation in (18) is derived by utilizing Monte Carlo sampling [12] technique.

Applying Monte Carlo integration to (18) derives

$$P(w^j\mid f_i)\approx\frac{\sum_{k=1}^{K}P_V(w^j\mid z_k)p_{\mathfrak{F}}(f_i\mid z_k)}{\sum_{h=1}^{K}p_{\mathfrak{F}}(f_i\mid z_h)} \tag{20}$$

-continued

$$= \sum_{k=1}^{K} P_V(w^j \mid z_k) x_k$$

where

$$x_k = \frac{P_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{h=1}^{K} P_{\mathfrak{F}}(f_i \mid z_h)}.$$

The words with the top highest $P(w^j|f_i)$ are returned to annotate the image. Given this image annotation scheme, the image-to-text retrieval may be performed by retrieving documents for the returned words based on traditional text retrieval techniques. For example, the returned word list may be a predetermined number of words, all words exceeding a probability threshold, or the set of words whose aggregate probabilities exceed a threshold, or a hybrid of these schemes.

Text-to-Image Retrieval

Traditional text-based image retrieval systems, such as the commercial Web search engines, solely use textual information to index images. It is generally accepted that this approach fails to achieve a satisfactory image retrieval, and this perceived failure has actually motivated the CBIR research. Based on the model obtained above to explicitly exploit the synergy between imagery and text, an alternative and much more effective approach to traditional CBIR, using the Bayesian framework to image retrieval given a text query, is provided.

Similar to the derivation in the Image Annotation and Image-to-Text Retrieval section above, we retrieve images for word queries by determining the conditional probability $P(f_i|w_j)$

$$\begin{aligned} P(f_i \mid w^j) &= \int P_{\mathfrak{F}}(f_i \mid z) P(z \mid w^j) dz \\ &= \int P_V(w^j \mid z) \frac{P_{\mathfrak{F}}(f_i \mid z) P(z)}{P(w^j)} dz \\ &= E_z \left\{ \frac{P_V(w^j \mid z) P_{\mathfrak{F}}(f_i \mid z)}{P(w^j)} \right\} \end{aligned} \tag{21}$$

The expectation can be estimated as follows:

$$\begin{aligned} P(f_i \mid w^j) &\approx \frac{\sum_{k=1}^{K} P_V(w^j \mid z_k) P_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{h=1}^{K} P_V(w^j \mid z_h)} \\ &= \sum_{k=1}^{K} P_{\mathfrak{F}}(f_i \mid z_k) y_k \end{aligned}$$

where

$$y_k = \frac{P_V(w^j \mid z_k)}{\sum_h P_V(w^j \mid z_h)}.$$

The images in the database with the top highest $P(f_i|w^j)$ are returned as the retrieval result for each query word.

Example 1

A prototype system was implemented in accordance with the framework set forth above. The architecture of the prototype system is illustrated in FIG. **2**, where the "image database" contains the training images as well as testing images; the "associated annotation" contains all the training annotation words. The process of probabilistic model fitting to generate the image-concept-word model (the shaded area in FIG. **2**) is processed offline; the text querying and image querying based on the Bayesian framework (the unshaded area in FIG. **2**) are performed online.

The system supported both image-to-text (i.e., image annotation) and text-to-image retrievals. As shown in FIG. **2**, the image-to-image querying also can be conducted in the system by incorporating the existing commercial text-based image search engines, i.e., the obtained annotation words for the query image are input into an text-based image search engine to retrieve images. Alternatively, the image-to-image retrieval may be conducted by first calling the image-to-text retrieval and then using the retrieved words to conduct the text-to-image retrieval collectively.

Of course, it is also possible to employ the prototype system to retrieve an image output set corresponding to an input image or image set, or to employ two prototype systems linked through either a word query linkage, or bypassing the output layer and linking the hidden layers of each system directly. Note that in this later system, there would be two hidden layers, the interconnections of which must be optimized separately. For example, two separate information domains, each comprising a set of images and words may be provided. Note that, while the formulation of the hidden concept layer is dependent on consistency of the semantic framework of the words used in training, the word usage need not be consistent between the two sets. Rather, the concepts "extracted" from the image-word relationships are anticipated to be consistent. The hidden concepts of the first domain are then mapped to the hidden concepts of the second domain using a second training process. For example, all or a portion of images of the first domain are submitted to the second domain and/or vice versa, and the interconnections of respective hidden concepts optimized to yield minimum error. Efficiencies are obtained by selecting or synthesizing training images for one or both domains which represent exemplars for respective hidden concepts. Alternately, preexisting common images in both domains may be employed to normalize the respective mapping. Further, it is also possible to map the word output of a complete prototype system to another prototype system. It is noted that in the general case, the word output will be considered normalized, and therefore no training or mapping will be required for use of the output of one network as the input for another network.

The word output of a network may be analyzed using traditional linguistic techniques, without departing from the scope and spirit of the present invention. Thus, for example, a semantic taxonomy may be employed to derive express concepts from the word output, or to modify the word input. Note that the express concepts need not be related to the hidden concepts, although according to general understanding, there will be some correlation.

When implemented in a search system, the input may include both an image and text. For example, an exemplar web page may serve as a starting point for retrieval of similar pages. Thus, a trained network may be used in a hybrid environment, as a text to image, image to text, image-to-image and text+image to image and/or text system. Typically, a text-to-text system would not employ the present invention, unless perhaps it is used as an automated language translation system, in which text input is converted to "concepts", which are then mapped to a different text output.

While the system according to the present invention can operate with unprocessed images, it may benefit from pre-processing of images. For example, textual features within images may be extracted using optical character recognition technology, and serve as a separate input or query. Object extraction processing may be used to separate various components from an image or stream, each of which may serve as a separate input or component of an input. Other types of processing may be employed to characterize or otherwise parse an input image. An advantage of separate preprocessing of the image is that, in some special cases, a heuristic or predefined feature extraction scheme may improve the semantic extraction performance of the composite Bayesian+object-based image annotation and retrieval system.

The processing of images using heuristics and/or object extraction processing schemes is known, and such known techniques may be advantageously used in accordance with the present invention.

Example 2

Dataset and Feature Sets

It has been noted that the data sets used in most recent automatic image annotation systems [1, 10, 11, 17] fail to capture the difficulties inherent in many real image databases. Thus, publications reporting performance based on artificially constrained data sets may not be comparable to those using less constrained or unconstrained data sets.

The commonly used Corel database, for example, is much easier for image annotation and retrieval than the unconstrained image data set due to its limited semantics conveyed and relatively small variations of visual contents. The typical small scales of the datasets reported in the literature are far away from being realistic in all the real world applications.

The prototype system according to the present invention was therefore evaluated on a collection of large-scale real world data automatically crawled from the Web, as an example of a minimally constrained image data set. The images and the surrounding text describing the image contents in web pages were extracted from the blocks containing the images by using the VIPS algorithm [4]. The surrounding text is processed using the standard text processing techniques to obtain the annotation words. Apart from images and annotation words, the weight of each annotation word for images was computed by using a scheme incorporating TF, IDF, and the tag information in VIPS, and was normalized to range (0,10). The image annotation word pairs were stemmed and manually cleaned before using as the training database for model fitting and testing. The data collection consisted of 17,000 images and 7,736 stemmed annotation words. Among them, 12,000 images were used as the training set and the remaining 5,000 images were used for the testing purpose. Compared with images in the Corel database, the images in this set were more diverse both on semantics and on visual appearance, which reflect the true nature of image search in many real applications. FIG. **3** shows an image example with the associated annotation words in the generated database.

The present example does not focus on image feature selection and the approach is independent of any visual features. As stated above, various image feature processing techniques may also be employed in conjunction with this technique. For implementation simplicity and fair comparison purpose, similar features to those used in [11] are used in the prototype system. Specifically, a visual feature is a 36 dimensional vector, consisting of 24 color features (auto correlogram computed over 8 quantized colors and 3 Manhattan Distances) and 12 texture features (Gabor energy computed over 3 scales and 4 orientations).

Experiment Design

To evaluate the effectiveness and the promise of the prototype system for image annotation and multi-model image retrieval, the following performance measures are defined:

- Hit-Rate3 (HR3): the average rate of at least one word in the ground truth of a test image is returned in the top 3 returned words for the test set.
- Complete-Length (CL): the average minimum length of returned words which contains all the ground truth words for a test image for the test set.
- Single-Word-Query-Precision (SWQP(n)): the average rate of relevant images (here 'relevant' means that the ground truth annotation of this image contains the query word) in the top n returned images for a single word query for the test set.

HR3 and CL measure the accuracy of image annotation (or the image-to-text retrieval); the higher the HR3, and/or the lower the CL, the better the annotation accuracy. SWQP(n) measures the precision of text-to-image retrieval; the higher the SWQP(n), the better the text-to-image retrieval precision.

Furthermore, we also measure the image annotation performance by using the annotation recall and precision defined in [11].

$$\text{recall} = \frac{B}{C} \text{ and precision} = \frac{B}{A},$$

where A is number of images automatically annotated with a given word in the top 10 returned word list; B is the number of images correctly annotated with that word in the top-10-returned-word list; and C is the number of images having that word in ground truth annotation. An ideal image annotation system would have a high average annotation recall and annotation precision simultaneously.

Results of Automatic Image Annotation

In the prototype system, words and their confidence scores (conditional probabilities) are returned to annotate images upon users' querying.

Applying the method of estimating the number of hidden concepts described above with respect to the training set, the number of the concepts was determined to be 262. Compared with the number of images in the training set, 12,000, and the number of stemmed and cleaned annotation words, 7,736, the number of semantic concept variables was far less.

In terms of computational complexity, the model fitting was a computation-intensive process; it took 45 hours to fit the model to the training set on a Pentium IV 2.3 GHZ computer with 1 GB memory. However, this process was performed offline and only once. For online image annotation and single word image query, the response time is generally acceptable (less than 1 second).

To show the effectiveness and the promise of the probabilistic model in image annotation, the accuracy of prototype system was compared with that of MBRM [11]. In MBRM, the word probabilities are estimated using a multiple Bernoulli model and no association layer between visual features and words is used. The prototype system was compared with

MBRM because MBRM reflects the performance of the state-of-the-art automatic image annotation research. In addition, since the same image visual features are used in MBRM, a fair comparison of the performance is expected.

FIG. **5** shows examples of the automatic annotation obtained by the prototype system and MBRM on the test image set. Here, the top 5 words (according to probability) are taken as automatic annotation of the image. It clearly indicates that the prototype system performs better than MBRM. The systematic evaluation results are shown for the test set in Table 1. Results are reported for all (7736) words in the database. The system implemented in accordance with the present invention clearly outperforms MBRM. As is shown, the average recall improves 48% and the average precision improves 69%. The multiple Bernoulli generation of words in MBRM is artificial and the association of the words and features is noisy. On the contrary, in accordance with the present invention, no explicit word distribution is assumed and the synergy between the visual features and words exploited by the hidden concept variables reduces the noises substantially.

TABLE 1

Performance comparison on the task of automatic image annotation on the test set

Models	MBRM	Our Model
HR3	0.56	0.83
CL	1265	574
#words with recall > 0	3295	6078
Results on all 7736 words		
Average Per-word Recall	0.19	0.28
Average Per-word Precision	0.16	0.27

The system in accordance with the present invention provides better performance. Some returned words with top rank from the prototype system for a given image are found semantically relevant by subjective examinations, although they are not contained in the ground truth annotation of the image. These words were not counted in the computation of the performance in Table 1; consequently, the HR3, recall, and precision in the table may actually be underestimated while the CL may be overestimated for the prototype system.

Results of Single Word Text-to-Image Retrieval The single word text-to-image retrieval results on a set of 500 randomly selected query words are shown in FIG. **4**. The average SWQP(2, 5, 10, 15, 20) of the prototype system and those of MBRM are recorded. A returned image is considered as relevant to the single word query if this word is contained in the ground truth annotation of the image.

It is shown that the performance of the probabilistic model in accordance with the present invention has higher overall SWQP than that of MBRM. It is also noticeable that when the scope of returned images increases, the SWQP(n) in the prototype system attenuates more gracefully than that in MBRM, which is another advantage of the present invention.

The present invention provides a probabilistic semantic model for automatic image annotation and multi-modal image retrieval. Instead of assuming artificial distribution of annotation word and the unreliable association evidence used in many existing approaches, the present invention assumes a hidden concept layer as the connection between the visual features and the annotation words, to explicitly exploit the synergy between the two modalities. The hidden concept

variables are discovered and the corresponding probabilities are determined by fitting the generative model to the training set.

The model fitting is performed in the criterion of MLE and an EM based iterative learning procedure is developed. Based on the model obtained, the image-to-text and text-to-image retrievals are conducted in a Bayesian framework, which is adaptive to the data set and has clear interpretation of confidence measures. The model according to the present invention may be advantageously used for image annotation and multi-model image retrieval, which was demonstrated by the evaluation of a prototype system on 17,000 images and the automatically extracted annotation words from crawled Web pages. In comparison with a state-of-the-art image annotation system, MBRM, the present invention shows a higher reliability and superior effectiveness.

In order to reduce training time, it may be possible to use sampling techniques and prior knowledge (e.g., category information of web pages).

APPENDIX A

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The invention claimed is:

1. A method of ranking multimedia works with respect to a query, comprising:

(a) storing, in a memory, information defining a conditional probability framework representing a plurality of concepts represented within at least two different media types of multimedia works comprising semantic concepts and visual feature concepts, based on analysis of at least a subset of the plurality of works;

(b) receiving a query comprising information defining at least one of the semantic concepts and the visual feature concepts;

(c) automatically determining a set of multimedia works of the at least two different media types corresponding to the at least one of said concepts associated with the query by associating semantic concepts of a first multimedia work with visual feature concepts of a second multimedia work as annotations, using a probabilistic framework comprising a visual feature layer, a semantic layer, and a hidden concept layer which connects the visual feature layer and the semantic layer, with at least one automated processor, wherein conditional probabilities of the visual feature concepts and the annotations given a hidden concept class are determined based on an Expectation-Maximization (EM) based iterative learning procedure;

(d) automatically ranking the determined set of multimedia works of the at least two different media types determined to correspond to the at least one of said concepts associated with the query in accordance with a relevance to the query according to a joint probability distribution which models a probability that the query associated with the at least one of said concepts is associated with a respective multimedia work, with the at least one automated processor; and

(e) at least one of (i) storing in the memory, and (ii) outputting information selectively dependent on the ranking.

2. The method according to claim **1**, the at least one of said concepts associated with the query is implicit; further comprising automatically mapping multimedia works to the conditional probability framework, using at least one processor, based on implicit concepts represented within each multimedia work, the probabilistic framework comprising at least one joint probability distribution which models a probability that a symbol belonging to a respective concept is an annotation symbol of a respective multimedia work.

3. The method according to claim **1**, wherein the conditional probability framework is organized according to semantic concepts, and the query comprises a multimedia work having implicit semantic concepts expressed in a non-semantic form.

4. The method according to claim **1**, wherein the query comprises an image, and wherein the image is processed to determine implicit semantic image content characteristics.

5. The method according to claim **1**, wherein at least one semantic word is associated with the received query as an implicit semantic concept, the probabilistic framework is a semantic probabilistic framework in which multimedia works are mapped to semantic concepts, and the at least one semantic word is used to search the mapped multimedia works within the probabilistic semantic framework.

6. The method according to claim **5**, wherein a plurality of words belong to at least one respective semantic concept, such that the association of the respective multimedia work with the plurality of semantic concepts is through automatically generated annotation words and analysis of the joint probability distribution.

7. The method according to claim **1**, wherein the query comprises an image, said at least two different media types comprise multimedia works comprising words and multimedia works comprising images having visual features, and said automatically determining comprises associating words with a respective image using a Bayesian model comprising the hidden concept layer which connects the visual feature layer and the word layer, which is discovered by fitting the generative model to a training set comprising images and annotation words, wherein the conditional probabilities of the visual features and the annotation words given the hidden concept class are determined based on the Expectation-Maximization (EM) based iterative learning procedure.

8. The method according to claim **7**, wherein f_i, $i \in [1,N]$ denotes a visual feature vector of images in a training database, where N is the size of the database, w^j, $j \in [1,M]$ denotes the distinct textual words in a training annotation word set, where M is the size of annotation vocabulary in the training database, the visual features of images in the database, $f_i=[f_i^1, f_i^2, \ldots f_i^L]$, $i\in[1, N]$ are known i.i.d. samples from an unknown distribution, having a visual feature dimension L, the specific visual feature annotation word pairs (f_i, w^j), $i\in[1, N]$, $j\in[1,M]$ are known i.i.d. samples from an unknown distribution, associated with an unobserved semantic concept variable $z\in Z=\{z_1, \ldots z_k\}$, in which each observation of one visual feature $f\in F=\{f_i, f_2, \ldots, f_N\}$ belongs to one or more concept classes z_k and each observation of one word $w\in V=\{w^1, w^2, \ldots, w^M\}$ in one image f_i belongs to one concept class, in which the observation pairs (f_i, w^j) are assumed to be generated independently, and the pairs of random variables (f_i, w^j) are assumed to be conditionally independent given the respective hidden concept z_k, such that $P(f_i, w^j|z_k)=p_{\mathfrak{F}}(f_i|z_k)P_V(w^j|z_k)$;

the visual feature and word distribution is treated as a randomized data generation process, wherein a probability of a concept is represented as $P_z(z_k)$;

a visual feature is selected $f_i\in F$ with probability $P_{\mathfrak{F}}(f_i|z_k)$; and a textual word is selected $w^j\in V$ with probability $P_V(w^j|z_k)$, from which an observed pair (f_i, w^j) is obtained, such that a joint probability model is expressed as follows:

$$
\begin{aligned}
P(f_i, w^j) &= P(w^j)P(f_i \mid w^j) \\
&= P(w^j)\sum_{k=1}^{K} P_{\mathfrak{F}}(f_i \mid z_k)P(z_k \mid w^j) \\
&= \sum_{k=1}^{K} P_z(z_k)P_{\mathfrak{F}}(f_i \mid z_k)P_V(w^j \mid z_k),
\end{aligned}
$$

and the visual features are generated from K Gaussian distributions, each one corresponding to a z_k, such that for a specific semantic concept variable z_k, the conditional probability density function of visual feature f_i is expressed as:

$$
P_{\mathfrak{F}}(f_i \mid z_k) = \frac{1}{2\pi^{L/2} \left|\sum_k\right|^{1/2}} e^{-\frac{1}{2}(f_i-\mu_k)^T \Sigma_k^{-1}(f_i-\mu_k)}
$$

where Σ_k and μ_k are the covariance matrix and mean of visual features belonging to z_k, respectively; and

word concept conditional probabilities $P_V(\bullet|Z)$, i.e., $P_V(w^j|z_k)$ for $k\in[1,K]$, are estimated through fitting the probabilistic model to the training set.

9. The method according to claim **8**, in which $P_{\mathfrak{F}}(f_i|z_k)$ is determined by maximization of the log-likelihood function:

$$
\log\prod_{i=1}^{N} p_{\mathfrak{F}}(f_i \mid Z)^{u_i} = \sum_{i=1}^{N} u_i \log\left(\sum_{k=1}^{K} P_z(z_k)P_{\mathfrak{F}}(f_i \mid z_k)\right)
$$

where u_i is the number of annotation words for image f_i and $P_z(z_k)$) and $P_V(w^j|z_k)$ are determined by maximization of the log-likelihood function:

$$
\mathfrak{L} = \log P(F, V) = \sum_{i=1}^{N}\sum_{j=1}^{M} n(w_i^j)\log P(f_i, w^j)
$$

where $n(w_i^j)$ denotes the weight of annotation word w^j, i.e., occurrence frequency, for image f_i; and

the model is resolved by applying the expectation-maximization (EM) technique, comprising:

(i) an expectation (E) step where the posterior probabilities are computed for the hidden variable z_k based on the current estimates of the parameters; and

(ii) an maximization (M) step, where parameters are updated to maximize the expectation of the complete-data likelihood log P(F,V,Z) given the posterior probabilities computed in the preceding E-step, whereby the probabilities can be iteratively determined by fitting the model to the training image database and the associated annotations.

10. The method according to claim **9**, wherein Bayes' rule is applied to determine the posterior probability for z_k under f_i and (f_i, w^j):

$$
p(z_k \mid f_i) = \frac{P_z(z_k)P_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{t=1}^{K} P_z(z_t)P_{\mathfrak{F}}(f_i \mid z_t)P_V(w^j \mid z_t)}
$$

$$
p(z_k \mid f_i, w^j) = \frac{P_z(z_k)P_z(f_i \mid z_k)P_V(w^j \mid z_k)}{\sum_{t=1}^{K} P_z(z_t)P_{\mathfrak{F}}(f_i \mid z_t)P_V(w^j \mid z_t)}
$$

and expectation of the complete-data likelihood log P(F,V,Z) for the estimated log P(F|V,Z) is

$$
\sum_{(i,j)=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M} n(w_i^j)\log[P_z(z_{i,j})P_{\mathfrak{F}}(f_i \mid z_{i,j})P_V(w^j \mid z_{i,j})]P(Z \mid F, V)
$$

where

$$
P(Z \mid F, V) = \prod_{s=1}^{N}\prod_{t=1}^{M} P(z_{s,t} \mid f_s, w^t)
$$

and the notation $z_{i,j}$ is the concept variable that associates with the feature-word pair (f_i, w^j).

11. The method according to claim **9**, wherein the expectation of the likelihood log P(F,Z) for the estimated P(Z|F) is expressed as:

$$
\sum_{k=1}^{K}\sum_{i=1}^{N} \log(P_z(z_k)P_{\mathfrak{F}}(f_i \mid z_k))p(z_k \mid f_i)
$$

and the expectation of log P(F,V,Z) and log P(F|V,Z) are maximized with Lagrange multipliers to $P_z(z_l)$, $p_{\Im}(f_u|z_l)$ and $P_V(w^v|z_l)$, under the normalization constraints

$$\sum_{k=1}^{K} P_z(z_k) = 1, \sum_{k=1}^{K} P(z_k \mid f_i, w^j) = 1$$

for any f_i, w^j, and z_l, the parameters being determined as

$$\mu_k = \frac{\sum_{i=1}^{N} u_i f_i p(z_k \mid f_i)}{\sum_{s=1}^{N} u_s p(z_k \mid f_s)}$$

$$\sum_k = \frac{\sum_{i=1}^{N} u_i p(z_k \mid f_i)(f_i \mid \mu_k)(f_i - \mu_k)^T}{\sum_{s=1}^{N} u_s p(z_k \mid f_s)}$$

$$P_z(z_k) = \frac{\sum_{j=1}^{M}\sum_{i=1}^{N} u(w_i^j) P(z_k \mid f_i, w^j)}{\sum_{j=1}^{M}\sum_{i=1}^{N} n(w_i^j)}$$

$$P_V(w^j \mid z_k) = \frac{\sum_{i=1}^{N} n(w_i^j) P(z_k \mid f_i, w^j)}{\sum_{u=1}^{M}\sum_{V=1}^{N} n(w_V^u) P(z_k \mid f_V, w^u)};$$

the number of concepts, K, is chosen to maximize

$$\log(P(F, V)) - \frac{m_K}{2}\log(MN)$$

where m_K is the number of free parameters needed for a model with K mixture components; and

$$m_K = (K-1) + K(M-1) + K(N-1) + L^2 = K(M+N-1) + L^2 - 1;$$

a joint distribution is used to model the probability of an event that a word w^j belonging to semantic concept z_k is an annotation word of image f_i:

$$P(w^j, z_k, f_i) = P_z(Z_k) p_{\mathfrak{F}}(f_i \mid z_k) P_V(w^j \mid z_k)$$

or

$$P(w^j \mid f_i) = \int P_v(w^j \mid z) p(z \mid f_i) dz$$

$$= \int P_V(w^j \mid z) \frac{p_{\mathfrak{F}}(f_i \mid z) P(z)}{p(f_i)} dz$$

$$= E_z\left\{\frac{P_v(w^j \mid z) p_{\mathfrak{F}}(f_i \mid z)}{p(f_i)}\right\}$$

where

$$p(f_i) = \int p_{\mathfrak{F}}(f_i \mid z) P_z(z) dz = E_z\{p_{\mathfrak{F}}(f_i \mid z)\}, \text{ and}$$

E_z {●} denotes the expectation over $P(z_k)$; and

a Monte Carlo integration is used to derive

$$P(w^j \mid f_i) \approx \frac{\sum_{k=1}^{K} P_V(w^j \mid z_k) p_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{h=1}^{K} p_{\mathfrak{F}}(f_i \mid z_h)}$$

$$= \sum_{k=1}^{K} P_V(w^j \mid z_k) x_k$$

$$\text{where } x_k = \frac{p_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{h=1}^{K} p_{\mathfrak{F}}(f_i \mid z_h)}$$

and wherein the words with the top highest $P(w^j|f_i)$ are returned to annotate the image.

12. The Bayesian model according to claim **9**, wherein images are retrieved for word queries by determining the conditional probability $P(f_i|w_j)$

$$P(f_i \mid w^j) = \int p_{\mathfrak{F}}(f_i \mid z) P(z \mid w^j) dz$$

$$= \int P_V(w^j \mid z) \frac{p_{\mathfrak{F}}(f_i \mid z) P(z)}{P(w^j)} dz$$

$$= E_z\left\{\frac{P_V(w^j \mid z) p_{\mathfrak{F}}(f_i \mid z)}{P(w^j)}\right\}$$

in which the expectation is estimated as follows:

$$P(f_i \mid w^j) \approx \frac{\sum_{k=1}^{K} P_V(w^j \mid z_k) p_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{h=1}^{K} P_V(w^j \mid z_h)}$$

$$= \sum_{k=1}^{K} p_{\mathfrak{F}}(f_i \mid z_k) y_k$$

$$\text{where } y_k = \frac{P_V(w^j \mid z_k)}{\sum_h P_V(w^j \mid z_h)}, \text{ and}$$

wherein the images in the database with the top highest $P(f_i|w^j)$ are returned as the retrieval result for each query word.

13. The method according to claim **2**, wherein the symbol comprises a word and the and the annotation symbol comprises an annotation word, wherein a plurality of symbols belong to at least one respective concept, such that the association of the respective multimedia work with implicit concepts is through automatically generated annotation symbols and analysis of the joint probability distribution.

14. A method of ranking a set of multimedia works, each multimedia work comprising at least a semantic concept and a non-semantic component, comprising:

(a) storing in a memory information defining a Bayesian model comprising a non-semantic feature layer, a semantic feature layer, and a hidden concept layer which connects the non-semantic feature layer and the semantic feature layer, adapted for probabilistically determining a set of semantic concepts inherent in the non-semantic components, based on contingent probabilities defined by the Bayesian model of associations of the respective semantic concepts and the respective non-semantic components of respective multimedia works, wherein the hidden concept layer is discovered by fitting a generative model to a training set comprising semantic concepts and non-semantic components, wherein the conditional probabilities of the semantic concepts and non-semantic components given a the hidden concept class are determined based on an Expectation-Maximization (EM) based iterative learning procedure;

(b) receiving at least one of a semantic and a non-semantic query;

(c) automatically and selectively determining a subset of the multimedia works corresponding to the query, with at least one automated processor, based on at least a relation of the query to the semantic concepts of the Bayesian model;

(d) ranking the determined subset based on a respective relevance of a respective multimedia work to the query; and

(e) at least one of storing and outputting, information selectively dependent on the ranked determined subset.

15. A method of ranking multimedia works with respect to a query, comprising:

(a) defining a probabilistic framework stored as information in a memory representing a plurality of concepts represented within at least two different media types of multimedia works, based on analysis of at least a subset of the plurality of works, the probabilistic framework comprising a Bayesian model for associating words with an image, comprising a hidden concept layer which connects a visual feature layer and a word layer which is discovered by fitting a generative model to a training set comprising image and annotation words, wherein the conditional probabilities of the visual features and the annotation words given a hidden concept class are determined based on an Expectation-Maximization (EM) based iterative learning procedure;

(b) receiving a query associated with at least one of said concepts;

(c) automatically determining a set of multimedia works of the at least two different media types corresponding to the query, with at least one automated processor, based on a relation of the at least one of said concepts associated with the query and the probabilistic framework;

(d) automatically ranking the set of multimedia works determined to correspond to the query in accordance with a relevance to the query, with the at least one automated processor; and

(e) at least one of storing and outputting information selectively dependent on the ranking.

16. The method according to claim **15**, wherein the Bayesian model comprises a semantic Bayesian framework representing an association of visual content with a plurality of semantic concepts, comprising at least one hidden layer formulated based on at least one joint probability distribution which models a probability that a word belonging to a respective semantic concept is an annotation word of respective visual content;

wherein a set of visual content is mapped to the semantic Bayesian framework dependent on semantic concepts represented in respective visual content, using at least one processor which automatically determines a set of annotation words associated with the respective visual content;

at least one implicit semantic concept is automatically extracted from a received query seeking elements of the set of visual content corresponding to at least one implicit semantic concept, using at least one processor;

elements of the mapped set of visual content corresponding to the at least one extracted implicit semantic concept are automatically determined, using at least one processor; and

the corresponding visual content is ranked in accordance with at least a correspondence to the at least one extracted implicit semantic concept.

17. The method according to claim **15**, wherein the hidden concept layer which connects a visual feature layer and a word layer which is discovered by fitting a generative model to a training set comprising images and annotation words, wherein the conditional probabilities of the visual content features and the annotation words given a hidden concept class are determined based on an Expectation-Maximization (EM) based iterative learning procedure.

18. The method according to claim **17**, wherein $f_i, i \in [1,N]$ denotes a visual feature vector of images in a training database, where N is the size of the database, $w^j, j \in [1,M]$ denotes the distinct textual words in a training annotation word set, where M is the size of annotation vocabulary in the training database, the visual features of images in the database, $f_i=[f_i^1, f_i^2, \ldots, f_i^L] i \in [1,N]$ are known i.i.d. samples from an unknown distribution, having a visual feature dimension L, the specific visual feature annotation word pairs $(f_i, w^j), i \in [1,N], j \in [1,M]$ are known i.i.d. samples from an unknown distribution, associated with an unobserved semantic concept variable $z \in Z=\{z_1, \ldots z_k\}$, in which each observation of one visual feature $f \in F=\{f_i, f_2, \ldots, f_N\}$ belongs to one or more concept classes z_k and each observation of one word $w \in V=\{w^1, w^2, \ldots w^M\}$ in one image f_i belongs to one concept class, in which the observation pairs (f_i, w^j) are assumed to be generated independently, and the pairs of random variables (f_i, w^j) are assumed to be conditionally independent given the respective hidden concept z_k, such that

$$P(f_i, w^j|z_k) = P_{\mathfrak{F}}(f_i|z_k) P_V(w^j|z_k);$$

the visual feature and word distribution is treated as a randomized data generation process, wherein a probability of a concept is represented as $P_z(z_k)$; a visual feature is selected $f_i \in F$ with probability $P_{\mathfrak{F}}(f_i|z_k)$; and a textual word is selected $w^j \in V$ with probability $P_V(w^j|z_k)$, from which an observed pair (f_i, w^j) is obtained, such that a joint probability model is expressed as follows:

$$\begin{aligned} P(f_i, w^j) &= P(w^j) P(f_i \mid w^j) \\ &= P(w^j) \sum_{k=1}^{K} P_{\mathfrak{F}}(f_i \mid z_k) P(z_k \mid w^j) \\ &= \sum_{k=1}^{K} P_Z(z_k) P_{\mathfrak{F}}(f_i \mid z_k) P_V(w^j \mid z_k), \end{aligned}$$

and the visual features are generated from K Gaussian distributions, each one corresponding to a z_k, such that for a specific semantic concept variable z_k, the conditional probability density function of visual feature f_i is expressed as:

$$P_{\mathfrak{F}}(f_i \mid z_k) = \frac{1}{2\pi^{L/2} \left| \sum_k \right|^{1/2}} e^{-\frac{1}{2}(f_i-\mu_k)^T \Sigma_k^{-1} (f_i-\mu_k)}$$

where Σ_k and μ_k are the covariance matrix and mean of visual features belonging to z_k, respectively; and word concept conditional probabilities $P_V(\bullet|Z)$, i.e., $P_V(w^j|z_k)$ for $k\in[1,K]$, are estimated through fitting the probabilistic model to the training set.

19. The method according to claim **18**, in which $P_{\mathfrak{F}}(f_i|z_k)$ is determined by maximization of the log-likelihood function:

$$\log\prod_{i=1}^{N} p_{\mathfrak{F}}(f_i\mid Z)^{u_i} = \sum_{i=1}^{N} u_i \log\left(\sum_{k=1}^{K} P_Z(z_k)p_{\mathfrak{F}}(f_i\mid z_k)\right)$$

where u_i is the number of annotation words for image f_i, and $P_z(z_k)$) and $P_V(w^j|z_k)$ are determined by maximization of the log-likelihood function:

$$\mathfrak{L} = \log P(F, V) = \sum_{i=1}^{N}\sum_{j=1}^{M} n(w_i^j)\log P(f_i, w^j)$$

where $n(w_i^j)$ denotes the weight of annotation word w^j, i.e., occurrence frequency, for image f_i; and

the model is resolved by applying the expectation-maximization (EM) technique, comprising:

(i) an expectation (E) step where the posterior probabilities are computed for the hidden variable z_k based on the current estimates of the parameters; and

(ii) an maximization (M) step, where parameters are updated to maximize the expectation of the complete-data likelihood log P(F,V,Z) given the posterior probabilities computed in the preceding E-step, whereby the probabilities can be iteratively determined by fitting the model to the training image database and the associated annotations.

20. The method according to claim **18**, wherein at least one of:

(A)

Bayes' rule is applied to determine the posterior probability for z_k under f_i and (f_i,w^j):

$$p(z_k\mid f_i) = \frac{P_Z(z_k)p_{\mathfrak{F}}(f_i\mid z_k)}{\sum_{t=1}^{K} P_Z(z_t)P_{\mathfrak{F}}(f_i\mid z_t)P_V(w^j\mid z_t)}$$

$$p(z_k\mid f_i, w^j) = \frac{P_Z(z_k)P_Z(f_i\mid z_k)P_V(w^j\mid z_k)}{\sum_{t=1}^{K} P_Z(z_t)P_{\mathfrak{F}}(f_i\mid z_t)P_V(w^j\mid z_t)}$$

and expectation of the complete-data likelihood log P(F,V, Z) for the estimated log P(F|V,Z) is

$$\sum_{(i,j)=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M} n(w_i^j)\log[P_Z(z_{i,j})p_{\mathfrak{F}}(f_i\mid z_{i,j})P_V(w^j\mid z_{i,j})]P(Z\mid F, V)$$

where

$$P(Z\mid F, V) = \prod_{s=1}^{N}\prod_{t=1}^{M} P(z_{s,t}\mid f_s, w^t)$$

and the notation $z_{i,j}$ is the concept variable that associates with the feature-word pair (f_i, w^j); and

(B)

the expectation of the likelihood log P(F,Z) for the estimated P(Z|F) is expressed as:

$$\sum_{k=1}^{K}\sum_{i=1}^{N}\log(P_Z(z_k)p_{\mathfrak{F}}(f_i\mid z_k))p(z_k\mid f_i)$$

and the expectation of log P(F,V, Z) and log P(F|V, Z) are maximized with Lagrange multipliers to $P_z(z_l)$, $p_{\mathfrak{F}}(f_u|z_l)$ and $P_V(w^v|z_l)$, under the normalization constraints

$$\sum_{k=1}^{K} P_Z(z_k) = 1, \sum_{k=1}^{K} P(z_k\mid f_i, w^j) = 1$$

for any f_i, w^j, and z_l, the parameters being determined as

$$\mu_k = \frac{\sum_{i=1}^{N} u_i f_i p(z_k\mid f_i)}{\sum_{s=1}^{N} u_s p(z_k\mid f_s)}$$

$$\sum_k = \frac{\sum_{i=1}^{N} u_i p(z_k\mid f_i)(f_i-\mu_k)(f_i-\mu_k)^T}{\sum_{s=1}^{N} u_s p(z_k\mid f_s)}$$

$$P_Z(z_k) = \frac{\sum_{j=1}^{M}\sum_{i=1}^{N} u(w_i^j)P(z_k\mid f_i, w^j)}{\sum_{j=1}^{M}\sum_{i=1}^{N} n(w_i^j)}$$

$$P_V(w^j\mid z_k) = \frac{\sum_{i=1}^{N} n(w_i^j)P(z_k\mid f_i, w^j)}{\sum_{u=1}^{M}\sum_{V=1}^{N} n(w_V^u)P(z_k\mid f_V, w^u)}.$$

21. The method according to claim **20**, in which the number of concepts, K, is chosen to maximize

$$\log(P(F, V)) - \frac{m_K}{2}\log(MN)$$

where m_K is the number of free parameters needed for a model with K mixture components;

and $m_K=(K-1)+K(M-1)+K(N-1)+L^2=K(M+N-1)+L^2-1$; and

wherein a joint distribution is used to model the probability of an event that a word w^j belonging to semantic concept z_k is an annotation word of image f_i:

$$P(w^j,z_k,f_i)=P_z(Z_k\,p_{\mathfrak{F}}(f_i|z_k)P_V(w^j|z_k)$$

or

$$P(w^j\mid f_i) = \int P_V(w^j\mid z)p(z\mid f_i)dz$$

-continued

$$= \int P_V(w^j \mid z) \frac{p_{\mathfrak{F}}(f_i \mid z) P(z)}{p(f_i)} dz = E_z\left\{\frac{P_V(w^j \mid z) p_{\mathfrak{F}}(f_i \mid z)}{p(f_i)}\right\}$$

where

$p(f_i) = \int p_{\mathfrak{F}}(f_i \mid z) P_z(z) dz = E_z\{p_{\mathfrak{F}}(f_i \mid z)\}$, and

$E_z\{\bullet\}$ denotes the expectation over $P(z_k)$; and

a Monte Carlo integration is used to derive

$$P(w^j \mid f_i) \approx \frac{\sum_{k=1}^{K} P_V(w^j \mid z_k) p_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{h=1}^{K} p_{\mathfrak{F}}(f_i \mid z_h)} = \sum_{k=1}^{K} P_V(w^j \mid z_k) x_k$$

$$\text{where } x_k = \frac{p_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{h=1}^{K} p_{\mathfrak{F}}(f_i \mid z_h)},$$

and wherein the words with the top highest $P(w^j|f_i)$ are returned to annotate the image.

22. The method according to claim **19**, wherein images are retrieved for word queries by determining the conditional probability $P(f_i|w_j)$

$$P(f_i \mid w^j) = \int P_{\mathfrak{F}}(f_i \mid z) P(z \mid w^j) dz = \int P_V(w^j \mid z) \frac{p_{\mathfrak{F}}(f_i \mid z) P(z)}{P(w^j)} dz = E_z\left\{\frac{P_V(w^j \mid z) p_{\mathfrak{F}}(f_i \mid z)}{P(w^j)}\right\}$$

in which the expectation is estimated as follows:

$$P(f_i \mid w^j) \approx \frac{\sum_{k=1}^{K} P_V(w^j \mid z_k) p_{\mathfrak{F}}(f_i \mid z_k)}{\sum_{h=1}^{K} P_V(w^j \mid z_h)} = \sum_{k=1}^{K} p_{\mathfrak{F}}(f_i \mid z_k) y_k$$

$$\text{where } y_k = \frac{P_V(w^j \mid z_k)}{\sum_h P_V(w^j \mid z_h)}, \text{ and}$$

wherein the images in the database with the top highest $P(f_i|w^j)$ are returned as the retrieval result for each query word.

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